JPRS-CST-91-005

27 FEBRUARY 1991

Foreign Broadcast Information Service

ANNIVERSARY 1941 - 1991

JPRS Report

Science & Technology

China

FUZZY LOGIC & NEURAL NETWORKS

CMOS FUZZY LOGIC CIRCUITS IN CURRENT-MODE TOWARD LARGE SCALE INTEGRATION

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ABSTRACT

CMOS current-mode circuit units are designed and fabricated completing various fuzzy logic operations and relevant processing. Experimental results show that these basic circuits have the advantages of simple structure, high functional density and high speed. They can be used as building blocks to achieve VLSI implementation of fuzzy hardwares. By the use of these circuit units a high speed fuzzy logic microprocessor for a real- time hardware expert system has been designed.

I. INTRODUCTION

Remarkable contributions have been made to the development, and applications of fuzzy set theory and fuzzy logic since Zadeh put forward the concept of fuzzy set for the first time (6). In recent years research and design of fuzzy hardwares such as fuzzy inference engine, fuzzy microprocessor using both discrete and integrated devices were reported and derives the beginning of fuzzy computers (1-4). Only a few research groups (2,5) designed and used basic bipolar or CMOS fuzzy logic circuits to build up their fuzzy hardwares, and others made out their fuzzy logic chips by conventional digital MOS IC's (2,3). Therefore simple- structure, reliable, high-speed basic circuit units are needed to implement various fuzzy logic operations. T. Yamakawa *et al* (5) reported nine current-mode fuzzy logic circuits in CMOS technology. Here we proposed simpler and more reliable circuit units implementing these nine fuzzy logic operations, as well as other useful circuits of which fuzzy logic and multiple-valued logic (MVL) integrated hardwares are made.

II. NINE FUZZY LOGIC OPERATIONS AND THEIR RELATIONS

Following described are the definations of most of the operations used in fuzzy logic and the relations among these operations. Let $x, y (0 \le x, y \le 1)$ denote membership functions of fuzzy sets, and $+, -$ stand for algebraic sum and subtraction, respectively.

1. Bounded-difference.

$$x \ominus y = \begin{cases} x - y & x \ge y \\ 0 & x < y \end{cases} \tag{1}$$

2. Complement.

$$\bar{x} = 1 - x \tag{2}$$

3. Union(Max).

$$x \vee y = \begin{cases} x & x \ge y \\ y & x < y \end{cases} \tag{3}$$

4. Intersection(Min).

$$x \wedge y = \begin{cases} y & x \ge y \\ x & x < y \end{cases} \tag{4}$$

5. Bounded-sum.

$$x \oplus y = \begin{cases} x + y & x + y \le 1 \\ 1 & x + y > 1 \end{cases} \tag{5}$$

6. Bounded-product.

$$x \odot y = \begin{cases} 0 & x + y \le 1 \\ x + y - 1 & x + y > 1 \end{cases} \tag{6}$$

7. Implication.

$$x \rightarrow y = \begin{cases} 1 - x + y & x \ge y \\ 1 & x < y \end{cases} \tag{7}$$

8. Absolute difference.

$$|x - y| = \begin{cases} x - y & x \ge y \\ y - x & x < y \end{cases} \tag{8}$$

9. Equivalence.

$$x \equiv y = \begin{cases} 1 - x + y & x \ge y \\ 1 - y + x & x < y \end{cases} \tag{9}$$

For the convenience of circuit realization of some of the above fuzzy logic operations, some necessary relations among these operations are dedicated below.

$$x \vee y = x + y \ominus x = y + x \ominus y \tag{10}$$

$$x \wedge y = x - x \ominus y = y - y \ominus x \tag{11}$$

$$x \oplus y = (x + y) \wedge 1 \tag{12}$$

$$x \odot y = (x + y) \ominus 1 \tag{13}$$

$$x \rightarrow y = 1 - x \ominus y \tag{14}$$

$$|x - y| = x \ominus y + y \ominus x \tag{15}$$

$$x \rightleftarrows y = 1 - |x - y| \tag{16}$$

III. CMOS CURRENT-MODE FUZZY LOGIC/MVL CIRCUIT UNITS

CMOS p- and n-channel current mirrors in Fig. 1(a1), (a2) are used to form the circuits of the above nine basic operations. Fig. 1(b1), (b2) are the simplified symbols for Fig. 1(a1), (a2), respectively. Fig. 2 shows the circuits of bounded-difference operation, where Fig. 2(a1) and (a2) give two circuits with different directions of output currents. Substituting p-(n-)channel current mirrors for n-(p-)channel ones in Fig. 2(a1), (a2) will create their complementary circuits shown in Fig. 2(b1), (b2). This circuitry complementarity means a great convenience for designers to use these fuzzy logic units as toy bricks in their circuit system without considering specific current directions between two neighbouring bricks. All the circuit units introduced in this paper are of this circuitry comlementarity. So the complementary ones of the following circuit units are omitted, leaving circuit units only with their input currents flowing into the units. With Eq. (10-16) and the bounded-difference circuits shown in Fig. 2 one can easily obtain the corresponding circuit units by adopting wired sum/subtraction. Fig. 3-10 show the circuits of fuzzy complement, union, intersection, bounded-sum, bounded-product, implication, absolute difference, and equivalence, respectively.

Since voltage-mode digital semiconductor memories are very mature and there are currently difficulties storing analog signals by semiconductor devices, conventional digital memories such as SRAM, PROM are prefered as peripheral circuits in fuzzy hardware systems (1-3). So the grade of fuzziness is discretized in 4 levels (i.e. 2 bits) or 8 levels (i.e. 3 bits) and so on. This multiple-bit voltage signal representing membership function of a fuzzy set will be converted into 1-bit current signal, say, 0μA standing for 000, 10μA for 001, ..., and 70μA for 111. To avoid the shift of transfering current through serially connected current mirrors a current-mode quantization circuit is needed which is shown in Fig. 11. The basic idea to design a current-mode register or flip-flop is to gain multiple-level stable states. This can be done by connecting the output of a quantizer with its input, forming a feedback loop. Fig. 12 shows the scheme of multiple-level stable states. The quantizer, register and flip-flop with multiple-level are also very useful in multiple-valued logic.

IV. RESULTS AND DISCUSSIONS

The nine fuzzy logic circuits contain only p-channel (L=5μm, W=30μm) and/or n-channel (L=5μm, W=20μm) MOS current mirrors. The others include current mirrors, current sources, convertors and transfer gates. The thickness of gate oxide and field oxide are 40nm and 800nm, respectively, while the threshold voltages V_{TP}=-1.15v, V_{TN}=0.77v. Measurement results show that all these circuit units can implement their corresponding fuzzy logic operations well. Here as an example, DC result of fuzzy logic union circuit is shown in Fig. 13. The time delay of this circuit is about 40ns. Diode formed by connecting gate with drain of a MOSFET is not included in our circuits, since our experiments show that a serially connected diode inside circuits has large resistance and makes an inevitable voltage drop, and in turn influences the normal logic function of the circuits. Every circuit described above has two kinds of format, which can be translated each other by the convertion between the p- and n-channel MOSFET. Circuit designers may choose one of the two forms of each circuit unit as a building block in their circuit system according to the current direction needed. There is no need to fix a current mirror between two adjacent circuit blocks in order to change a current direction. This will eliminate a time delay and current shift stage. Circuit units implementing bounded-difference, fuzzy logic union, intersection, quantization, register, and flip-flop have been applied to building up a high-speed fuzzy logic microprocessor for a real- time expert system in the field of robotic decision-making (1).

V. CONCLUSIONS

Basic circuit units in current-mode are designed and fabricated in 5 micron CMOS technology. They can implement various fuzzy logic operations of bounded-difference, complement, union(max), intersection(min), bounded-sum, bounded-product, implication, absolute difference, equivalence. Also fabricated are current quantizer, register and flip-flop which are of importance in building up a fuzzy information processing machine or a multiple- valued logic hardware. Test of chips show that by use of these basic circuits one can realize the corresponding logical functions very well. They exhibit the distinctive features of simple structure, high functional density, usage in multiple- valued logic integrated circuits, and a great convenience for high-density integration. These circuit units have great potential to be one of the best circuit architecture to form fuzzy logic and multiple-valued logic very large scale integrated (VLSI) hardwares.

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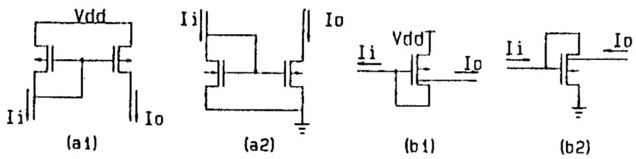
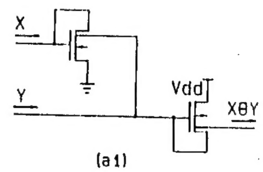


Fig.1 (a1) PMOS current mirror circuit (a2) NMOS current mirror circuit
(b1) Symbol of (a1) (b2) Symbol of (a2)



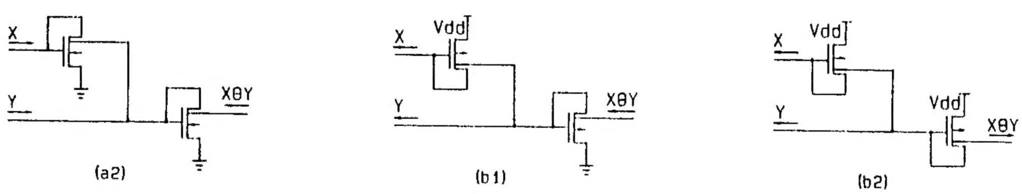


Fig.2 Bounded-difference circuit with various
(a1)—(b2) input and output current directions

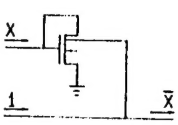


Fig.3 Complement circuit

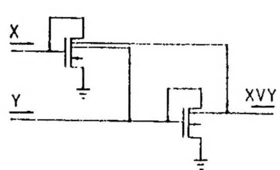


Fig.4 Union (Max) circuit

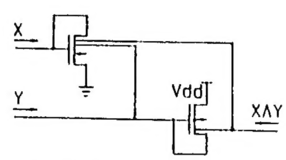


Fig.5 Intersection (Min) circuit

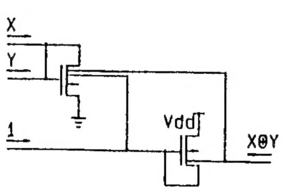


Fig.6 Bounded-sum circuit

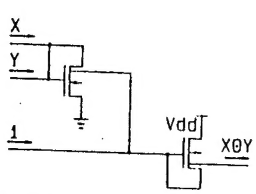


Fig.7 Bounded-product circuit

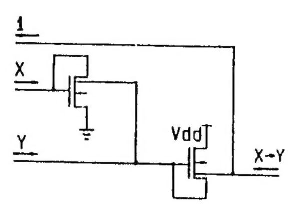


Fig.8 Implication circuit

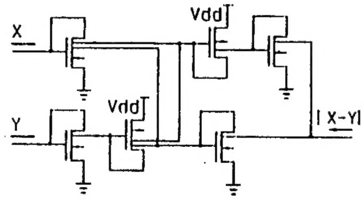


Fig.9 Absolute-difference circuit

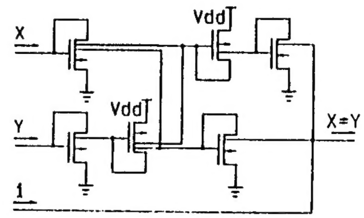


Fig.10 Equivalence circuit

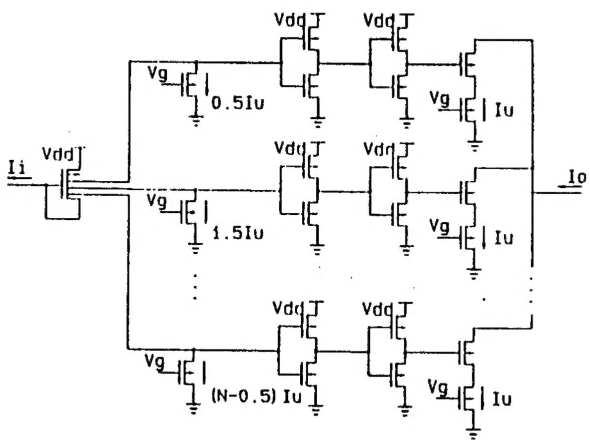


Fig.11 Quantization circuit

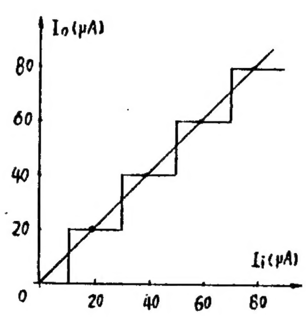


Fig.12 Scheme of multiple-level stable states employing feedback

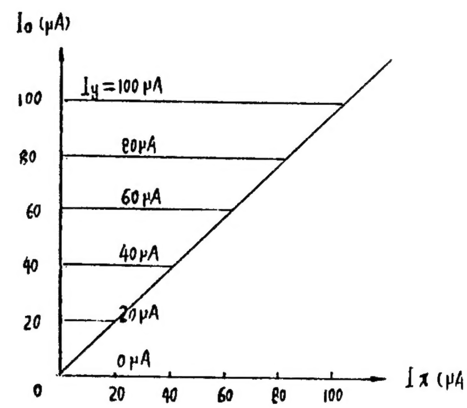


Fig.13 Input-output characteristics of union (max) circuit

AN APPLICATION OF QUANTUM THEORY TO NEURAL NETWORK

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ABSTRACT

Back propagation rule has been shown to be an efficientlearning algorithm for multilayerd neural network. However,it is limited because it only finds local minima. Boltzmann machine has also been shown to be an efficient learning rule. But,it is limited because it learning rate is too slow. In thispaper,we proposed and simulayed a quantum learning algorithm for multilayerd neural network.it is shown that its learning rate is more rapid than that of Boltzmann machine,and it can find theglobal minimun unlike back propagation algorithm does.

INTRODUCTION

The error backpropagation rule would modify the weight between neurons and j of m-th layer and (m-1)th layer,respectively, as follows:

$$\Delta W^m_{ij} = \rho\, \delta^m_i O^{m-1}_j \tag{1}$$

where ρ is an acceleration constant that relates to the stepsize of the simulation. The output of k-th neuron is q_k,its input is p_k, and δ_k is the backpropagation error given for final layer, n, by

$$\delta^n_i = f'(P^n_i)(u_i - t_i) \tag{2}$$

and for all other layers by

$$\delta^m_i = f'(P^m_i)\sum_k \delta^{m+1}_k W^{m+1}_{ik} \tag{3}$$

The error backpropagation rule has been shown to be an efficient learning algorithm for multilayerd neural network.However,it is limited for it only finds local minimas.Learning in a Boltzmann machine has two phases. In the training phase a binary input pattern is imposed as well as the correct binary out put pattern on the out put group .The system is allowed to relax to equilibrum at fixed 'temperature' while the inputs and outputs are held fixed. In equilibrium, the average fraction of the time a pair of units is on together,i.e.the co-occurrence probability p^+_{ij}, is computed for each connection. In the test phsae the same procedure is for-co-occurrence probabilities, p^-_{ij}, are again computed.The weights are then updated according to:

$$\Delta W_{ij} = \varepsilon\,(P^+_{ij} - P^-_{ij}) \tag{4}$$

where ε controls the rate of learning.

Similarly, Boltzmann machine has also been shown to be an efficient learnihg rule for multilayerd neural network. But,it is limited for its rate of learning is too slow.
In this paper, according to ITO stochastic differential equation:

$$d\xi = -\nabla f(\xi)dt + \epsilon\, dw \tag{5}$$

where ∇f is the gradient of f and w(t) is a standard n-dimensional Wiener process, where $\epsilon = \epsilon_o$ is a constant, we proposed and simulated a quantum learning algorithm for multi-layerd neural netweek which can find global minimum and coverge rapidly.

A QUANTUM LEARNING ALGORITHM

Consider equation as follows:

$$d\xi = -\nabla f(\xi)dt + \epsilon(t)dw \qquad (6)$$

$$\xi(0) = x_o \qquad (7).$$

Without the loss of generality, we assume that

$$\lim_{\|x\|^2 \to \infty} f(x) = +\infty$$

$$\int_{R^n} \exp[-\alpha^2 F(X)]dX < \infty, \forall \alpha \in R \setminus \{0\}$$

$$f: R^n \to R$$

To integrate numeroocally equations (6) and (7), let us look at the asymptotic value of a sampled numerical trajectory solution to obtain a global minimium off. Firstly, consider equations (6) and(7), when $\epsilon = \epsilon_o$ is a constant.

$$d\xi = \nabla f(\xi)dt + \epsilon_o dw(t) \qquad (8)$$

Let $\xi_{\epsilon_o}(t)$ be the stoohastio prooess solution of (8) and (7); for any Borel set $A \subset R^n$, define

$$P_{\epsilon_o}(0, x_o, t, A) = P(\xi_{\epsilon_o}(t) \in A) \qquad (9)$$

where $P(\cdot)$ is the probability of $(\cdot)$ and $P_{\epsilon_o}(0, x_o, t, A)$ is thetransition probability of $\xi_{\epsilon_o}(t)$. Under regularity assumptionsfor f, we have

$$P_{\epsilon_o}(0, x_o, t, A) = \int_A p_{\epsilon_o}(0, x_o, t, x)dx \qquad (10)$$

where the transition probability density $p = p_{\epsilon_o}(0, x_o, t, x)$ satifies the following Fokker-Planck equation

$$\partial p / \partial t = (\epsilon_o^2/2)\Delta p + \mathrm{div}(\nabla f p) \qquad (11)$$

with

$$\lim_{t \to \infty} p_{\epsilon_o}(0, x_o, t, x) = \delta(x - x_o) \qquad (12)$$

where Δ and div are the Laplacian and the divergence with respeot to x, and $\delta(\cdot)$ is the Dirac delta function. Let A_{ϵ_o} be defined by

$$1/A_{\epsilon_o} = \int_{R^n} \exp[-2f(x)/\epsilon_o^2]dx < \infty \qquad (13)$$

then as $t \to \infty$, the trandition probability density $p_{\epsilon_o}(0, x_o, t, x)$ approaches to the function

$$p_{\epsilon_0 \infty}(0, x_o, x) - A_{\epsilon_o}\exp[-2f(x)/\epsilon_o^2] \qquad (14)$$

Clearly, $p_{\epsilon_{0\infty}}$ is the probability density of a random variable $\xi_{\epsilon_{0\infty}}$ so that $\xi_{\epsilon_o}(t) \to \xi_{\epsilon_{0\infty}}$ when $t \to \infty$ due to (6) and (7). Let us remark that $p_{\epsilon_{0\infty}}$ does not depend on the initial condition x_o.

From the reasoning above, we can obtain that, as $\epsilon_o \to 0$, the the asymptotic probability density approaches to a Dirac delta fanction concentrated on the global minimum or a linear combination of dirac delta functions concentrated on the global the golbal minima. The linear combination depends on the curvatures of f at the global minima.

We can also obtain that, when

$$\lim_{t \to \infty} \epsilon(t) = 0 \tag{15}$$

and following equation is satisfied,

$$\int_0^{\infty} \exp(-[2/\epsilon^2(t)] \Delta f_+) dt = \infty \tag{16}$$

where Δf_+ is the highest barrier to the global minima, we can find the global minima of f(x) according (6). From (16), we know that $\epsilon(t)$ must go to zero slowly.

From above, the (6) can be easily used to train multilayered neural network. Let

$$f = E = \sum_i (O_i - t_i)^2$$

where o_i is actual output of i-th neuron of network, t_i is the desired output of i-th neuron of network. And let

$$\Delta t_k > 0, \; t_k = \sum_{i=0}^{k} \Delta t_i \; (t_0 = 0), k = 0, 1, \cdots$$

we can discretize (6) using the Euler-Cauchy method, that is, $\xi(t)$ is approximated by the ξ_k solution of the following finite difference equations,

$$\xi_{k+1} - \xi_k = -\Delta t_k \nabla f(\xi_k) + \epsilon(t_k)(W_{k+1} - W_k), k = 0, 1, \cdots, \tag{17}$$

$$\xi_o = x_o \tag{18}$$

In the (17), w_{ij}, ρ and w_k substitute for ξ_k, Δt_k and w_k, we can obtain the general form of quantum learning rule as follows

$$W_{ij}(k+1) - W_{ij}(k) = -\rho \nabla f(W_{ij}(k)) + \epsilon(M_{k+1} - M_k) \quad k = 0, 1, \cdots, \tag{19}$$

SIMULATION RESULT

We use a three-layer neural network and train it to function shift register. The training rules we have used are errorbackpropagation, Boltzmann machine and Quantum learning ones, the simulation result is shown in FIG.1. Clearly, from FIG.1, the rate of learning of Quantum rule is much more rapid than that of Boltzmann machine. The Quantum rule can find the global minima as proven above. Quantum learning algorithm has been used to train multilayered neural netword to recognize ship silhouettes.

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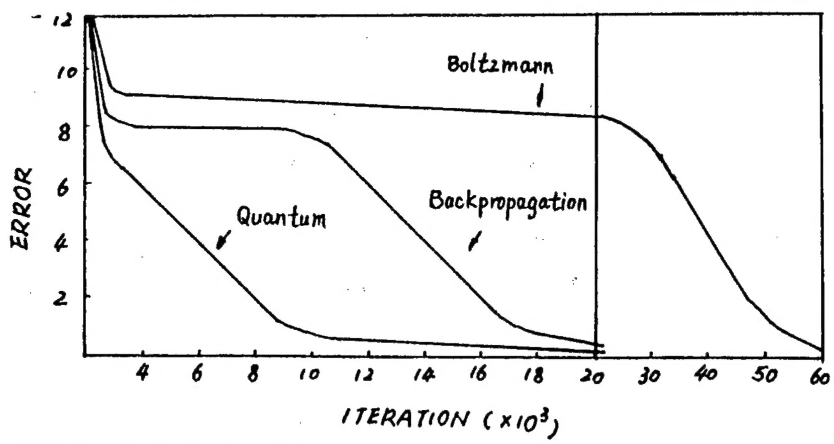

FIG.1. Simulation Results

THE TRUTH-VALUED FLOW INFERENCE NETWORK

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ABSTRACT

The conventional fuzzy inference uses the fuzzy relation and the compositional rule of inference method. But there is a limitation for the fuzzy relation to represent complex knowledge and complicated control rules in fuzzy control systems. A new fuzzy inference method has been proposed as an alternative namely Truth-valued Flow Inference method. By this method a proposition is regarded as a channel along which the truths can flow and the fuzzy inference is realized as such a process that the truth values flow along an inference channel from the top(precedence) to the end(antecedence). The truth value may decrease when flowing along the channel because there exists resistance in the channel. In this paper we make use of the concept of neural logic network to construct a Truth-Valued Flow Inference Network(TVFIN), extending the truth-valued flow inference to a neural network form. By the TVFIN it is flexible to represent knowledge and control rules in fuzzy control and carry out the fuzzy inference effectively.

KEYWORDS: Approximate Reasoning, Fuzzy Inference, Fuzzy relation, Fuzzy Control, Neural Network.

1. INTRODUCTION

After the fuzzy sets theory coming into the logic[14][15], the reasoning is no longer only true or false, yes or no as it is in the conventional logic. Fuzzy inference, as an approximate reasoning, has progressed rapidly in the last two decades.

The pattern of fuzzy inference is

$$\frac{\begin{array}{c} P \longrightarrow Q \\ P' \end{array}}{Q'} \tag{1}$$

The concept of fuzzy inference is as the following:

Assume that $P(x)(x \in X)$ and $Q(y)(y \in Y)$ are two fuzzy linguistic proposition in the universe of discourses X and Y respectively, when given implication $P \longrightarrow Q$, and a precedence P' which is approximately near to P, what Q' is to be deducted from the implication $P \longrightarrow Q$?

In 1973, L. A. Zadeh[15] used the fuzzy relation to model the fuzzy linguistic implication, carrying out a method of fuzzy inference namely the Compositional Rule of Inference(CRI) in which the fuzzy inference is the compositional calculation of the fuzzy relation.

In CRI method, the implication $P \longrightarrow Q$ is described as a fuzzy relation from X to Y, denoted by R. The CRI method is a fuzzy transformation as follows,

$$Q' \equiv P' o R \quad (2)$$

$$Q'(y) \equiv (P' o R)(y) \quad (3)$$

There have been many literatures discussing the definition of fuzzy relation R which express the fuzzy implication, more then 50 different definition of R and their compositional rules are available. The most worthwhile works in this area are made by Gaines R. R.[2], Bandler J. F.[1], Kandel A. and Cao Z. [6] and Mizumoto M. and Zimmermann H. J. [8], e.c.t.

In the fuzzy implication $P \longrightarrow Q$, when the antecedence Q is directly related to the precedence P, the fuzzy relation R can model the fuzzy implication effectively. For example, the simple fuzzy implication

$$\text{if } A \text{ then } B \quad (4)$$

or

$$\text{if } A \text{ and } B \text{ the } C \quad (5)$$

can be modelled by fuzzy relation R.

For (4) $$R = A \, X \, B \quad (6)$$

For (5) $$R = A \, X \, B \, X \, C \quad (7)$$

However, in the opinion of authors of [12] and [13], the fuzzy implication is the expression of the human knowledge, some times it is very complicated. The antecedence may not be directly related to the precedence, there may be many branches which cross each other. That is to say, the framework of knowledge is a complicated network. In this case, the fuzzy relation R can not represent the knowledge effectively. Moreover, for every branch of implications there should

be a certainty degree which may be dynamic other than static. The fuzzy relation theory also cannot deal with the dynamic process.

To create a new way of fuzzy inference to overcome the limitation of fuzzy relation method, the authors of [12] and [13] proposed a different method of fuzzy inference namely Truth-Valued Flow Inference method. In the truth-valued flow inference, a proposition or fuzzy implication is regarded as a channel along which the truth value can flow, and the fuzzy inference is viewed as such a process that the truth values flow along an inference channel from the top(precedence) to the end(antecedence). The truth value may decrease when flowing along the channel because there exists resistance in the channel.

According to the truth-valued flow inference method, for the implication $P \longrightarrow Q$, the truth value of Q is a function of the truth value of P , i.e.

$$T(Q) = f(T(P)) \tag{8}$$

where $T(Q)$ is the truth value of Q .

Here the head of the inference channel is P , the terminal of it is Q . The function $f(x)$ expresses the certainty degree of the proposition. If the $f(x)$ is given by a differential equation, the fuzzy inference can be treated as a dynamic process.

The procedures of fuzzy inference are as follows according to the truth-valued flow inference method:

1) Build up a channel set base which comprises a limited number of channels: $P_i \longrightarrow Q_i$ $(i=1, 2, ..., n)$, which represent the knowledge.
2) The given information is to form a fact P'_i which is a fuzzy set on the universe of discourses X. The truth value of P_i' is its nearness to P_i . $T(P_i')=near(P_i', P_i)$. $T(P_i')$ will be the input to the channel and the output of the channel will be calculated by (8).
3) The output of the channels is to be processed to do the decision making.

The above is called three steps of inference. The important thing of this method is that the output of one channel can be the input of the other, the channels can link each other and hence forming an inference network among which there may be many media relay stations of truth value transformation. By this way, the complex knowledge or control rules in fuzzy controller can be represented effectively.

Actually the truth-valued flow inference method has suggested a framework of inference network which is something like the neural network. So the authors

in this paper make use of the concept of the neural network to convert the truth-valued flow inference into a neural network form to construct a Truth-Valued Flow Network(TVFIN).

Various neural network models have been proposed and studied by many researchers. These models such as Crossbar Associative Network[10], Adaptive System[3], Boltzmann Machines[4], Self-organization and Associative Memory[11] and Neocognitrins[7] are powerful tools for the study of pattern processing. However, to model human knowledge, besides pattern processing capability, the logical reasoning capability is equally important. Another new neural network called Neural-logic Network which is able to do the logical reasoning is proposed by Prof. Teh H. H. et al.[5] Because the fuzzy inference is a fuzzy logical reasoning, we utilize the Neural-logic Network structure in TVFIN.

2. THE TRUTH-VALUED FLOW INFERENCE NETWORK

The TVFIN is defined as a multi-layer network consisting of a set of nodes represented by small circles drawn on a plane and a set of directed arcs linking some related pairs of nodes. Each node stand for a fuzzy subset of a linguistic variable. Every link is attached with an ordered pair of real numbers as its weightage. The nodes stand for the input linguistic variables are called input nodes, those that stand for the output variables are called output nodes and the rest are called the hidden nodes which stand for the median variables. An example of the TVFIN is shown in Fig. 1.

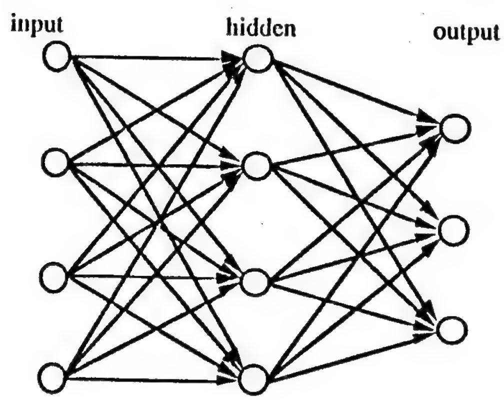

Fig. 1 The structure of the TVFIN

Each node can be assigned an real number $\mu \in [0,1]$, which represents the truth value(membership degree) of a fuzzy linguistic variable. Both real numbers

of the ordered pair for the weightage of each link is between $[-1, 1]$. The network is activated by assigning a truth value in [0,1] to the input nodes. The fuzzy inference is such a process that the truth values flow from the input nodes to the output nodes according to the rule of propagation. The propagation rule is defined as follows:

Let P be a given node of the network. Let $P_1, P_2, \ldots\ldots, P_n$ be all possible nodes which have links to the nodes P. Truth values associated with the node Pi is denoted by μ_i and that associated with P by μ_0, and the weightage for the link connecting Pi to P is denoted by (a_i, b_i), $a_i, b_i \in [-1, 1]$. The network is shown in Fig. 2.

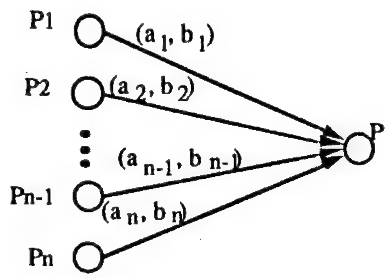

Fig. 2 The rule of propagation of TVFIN

The μ_o, the truth value of output P, is calculated by the following formula:

$$\mu_o = \left| \left|\bigvee_{i=1}^{n}(\mu_i * a_i)\right| - \left|\bigvee_{i=1}^{n}(\mu_i * b_i)\right| \right| \tag{9}$$

It is required that all a_i(or b_i) of links to a node be of the same sign(a_i and b_i may not be of the same sign), this is for the convenience of modelling the fuzzy control rules in fuzzy controllers.

In the example of Fig. 3, the left side can be simplified as the right side. Where

$$a'_1 = a_1 * |a-b|, \; b'_1 = b_1 * |a-b|$$
$$a'_2 = a_2 * |a-b|, \; b'_2 = b_2 * |a-b| \tag{10}$$

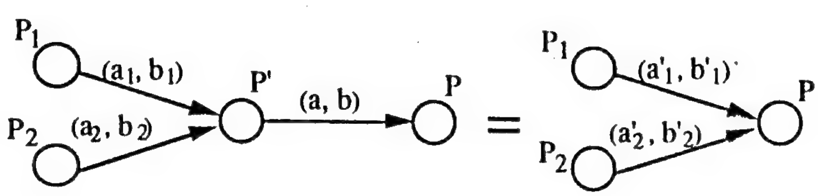

Fig. 3

In fuzzy logic the union, the intersection and the negation are the basic operations. Let's see how these operations are modeled by the TVFIN.

1). The union operation. $\mu_o=\mu_1 \vee \mu_2=max(\mu_1, \mu_2)$.(see Fig.4)

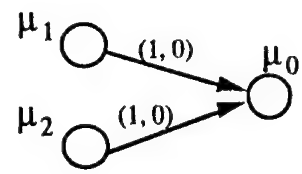

Fig. 4 The union operation

2). The intersection operation. $\mu_o=\mu_1 \wedge \mu_2=min(\mu_1, \mu_2)$. (see Fig. 5)

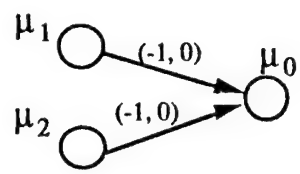

Fig. 5 The intersection operation

3). The negation operation. $\mu_o=1-\mu_1$.(see Fig. 6)

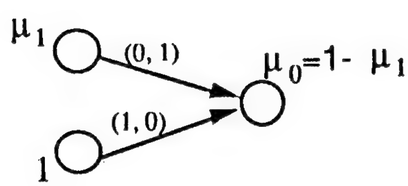

Fig. 6 The negation operation

3. THE TVFIN IN FUZZY CONTROL

Fuzzy controller is proposed as an alternative to the conventional or modern control methods when a system to be controlled is mathematically ill-understood or intractable. Modern control theory always relies on the precise mathematical model of a controlled system. Fuzzy controller simply imitate the control strategy of a human operator and it is unnecessary to know the mathematical model.

In a manual control system, human operator's strategy to control the process can be expressed in a set of control rules, for example,

if ERROR is PL and CHANGE IN ERROR is NM then CONTROL is PL
and ect.

Where *ERROR, CHANGE IN ERROR* are linguistic variables of input and *CONTROL* is that of output, they are defined as

$$\begin{aligned} &ERROR=\{PL, PM, PS, ZO, NS, NM, NL\} \\ &CHANGE\ IN\ ERROR=\{PL, PM, PS, ZO, NS, NM, NL\} \\ &CONTROL=\{PL, PM, PS, ZO, NS, NM, NL\} \end{aligned} \tag{11}$$

where *PL, PM, PS, ZO, NS, NM, NL* are fuzzy subsets, meaning *positive large, positive medium, positive small, zero, negative small, negative medium* and *negative large* respectively.

Generally, assume that there are two inputs linguistic variables A and B, and one single output linguistic variables C, with their universes of discourse being X, Y and U respectively.

$$A=\{A_i\} \in \mathcal{F}(X),\ (i \in I) \tag{12}$$

$$B=\{B_j\} \in \mathcal{F}(Y),\ (j \in J) \tag{13}$$

$$C=\{C_k\} \in \mathcal{F}(U),\ (k \in K) \tag{14}$$

where $I=\{1, 2, \cdots, m\}$, $J=\{1,2, \cdots, n\}$, $K=\{1, 2, \cdots, h\}$, $\mathcal{F}(X)$ represents the fuzzy power set of X.

The human operator's control strategy is usually described in terms of a set of multi-complexed linguistic implications as follows:

$$\begin{aligned} &If\ A\ is\ A_i\ and\ B\ is\ B_j\ then\ C\ is\ C_k \\ &(i \in I, j \in J, k = \varphi(i, j) \in K) \end{aligned} \tag{15}$$

Usually, the fuzzy relation theory and compositional rule of inference method(CRI method) is adopted to design fuzzy controllers since Mamdani and Assilian constructed the first fuzzy controller in 1974[9].

When using the fuzzy relation theory and compositional rule of inference method the above fuzzy implications can be translated into a three-dimensional fuzzy relation R as follows:

$$R \equiv \bigcup_{i,j} (A_i \times B_j \times C_k)$$

$$R \in \mathcal{F}(X \times Y \times U), \qquad (16)$$
$$R(x, y, u) = \bigvee_{i,j} (A_i(x) \wedge B_j(y) \wedge C_k(u)).$$
$$(k = \varphi(i, j) \in K)$$

where $R(x, y, u)$, $A_i(x)$, $B_j(y)$ and $C_k(u)$ are the membership functions of R, A_i, B_j and C_k respectively. The fuzzy controller is shown in Fig. 7.

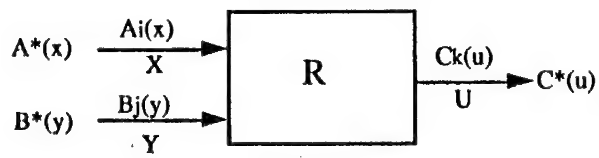

Fig.7 Fuzzy relation in fuzzy controller

Suppose that the inputs of the fuzzy controller at a certain instance are fuzzy sets $A^* \in \mathcal{F}(X)$, $B^* \in \mathcal{F}(Y)$, according to the CRI method, the output of the controller will be the fuzzy set $C^* \in \mathcal{F}(U)$, i.e

$$C^* = (A^* \times B^*) \circ R$$
$$C^*(u) = \sup_{\substack{x \in X \\ y \in Y}} (A^*(x) \wedge B^*(y) \wedge R(x, y, u))$$
$$= \sup_{\substack{x \in X \\ y \in Y}} ((A^*(x) \wedge B^*(y)) \wedge (\bigvee_{i,j} (A_i(x) \wedge B_j(y) \wedge C_{\varphi(i,\, j)}(u))))$$
$$= \sup_{\substack{x \in X \\ y \in Y}} (\bigvee_{i,j} ((A^*(x) \wedge A_i(x)) \wedge (B^*(y) \wedge B_j(y)) \wedge C_{\varphi(i,\, j)}(u)))$$
$$= \bigvee_{i,j} \sup_{x \in X}((A^*(x) \wedge A_i(x)) \wedge \sup_{y \in Y}(B^*(y) \wedge B_j(y)) \wedge C_{\varphi(i,\, j)}(u) \qquad (17)$$

In actual applications the inputs of the controller(i.e observed values of the controlled process) are some definite real numbers. Suppose in a certain instance the observed value is a pair (x_o, y_o), then the fuzzy sets of inputs A^* and B^* are as follows,

$$A^*(x) = \begin{cases} 1, & x=x_o \\ 0, & x \neq x_o \end{cases}, \quad B^*(y) = \begin{cases} 1, & y=y_o \\ 0, & y \neq y_o \end{cases} \qquad (18)$$

so that $$\sup_{x\in X}(A^*(x) \wedge A_i(x)) = A_i(x_o) \tag{19}$$

$$\sup_{y\in Y}(B^*(y) \wedge B_j(y)) = B_j(y_o) \tag{20}$$

therefore $$C^*(u) = \bigvee_{i,j} (A_i(x_o) \wedge B_j(y_o)) \wedge C_{\varphi(i,\ j)}(u) \qquad (i \in I, j \in J, \varphi(i, j) \in K) \tag{21}$$

or $$C^*(u) = \bigvee_{k\in K} \left(\bigvee_{\varphi(i,\ j)=k} (A_i(x_o) \wedge B_j(y_o)) \wedge C_k(u)\right) \qquad (i \in I, j \in J, \varphi(i, j) \in K) \tag{22}$$

Using the defuzzification method of Center-C-Gravity, the actual output of the fuzzy controller is,

$$u_o = \sum_{k\in K} \left(\bigvee_{\varphi(i,\ j)=k} (A_i(x_o) \wedge B_j(y_o))\right) * u_k \qquad (i \in I, j \in J, k=\varphi(i, j) \in K) \tag{23}$$

where the u_k is the gravity center of $(A_i(x_o) \wedge B_j(y_o) \wedge C_k)$.

We can see that , the above method of fuzzy inference in fuzzy controller is very simple and easy to understand. This is the reason that it is widely used in practice.

Let's examine the control rules in equ. (5), there is not any median linguistic variables between the inputs and the output variables. But in many complicated industrial processes, when describing the human control strategy, some median variables may be required. For example, a process concludes several different sections each of which is operated by different person, when describing the control strategy of the system each person can only note down the behavior of each section and he does not know the relation between the inputs and outputs of the whole system. So we need some median variables. In such cases, how to translate the control rules into a fuzzy relation R becomes a difficult problem. Even if the R is available, it is still too complicated to calculate the composition of the fuzzy inference.

For instance, consider a set of rules as follows

$$
\begin{aligned}
&\text{if } A=A_1 \text{ and } B=B_3 \text{ then } C=C_2 \text{ and } D=D_1\\
&\text{if } A=A_2 \text{ and } B=B_1 \text{ then } D=D_2 \text{ and } E=E_2\\
&\text{if } A=A_3 \text{ then } C=C_1 \text{ and } E=E_1\\
&\qquad\text{if } B=B_2 \text{ and } C=C_1 \text{ then } D=D_2\\
&\qquad\qquad\text{if } C=C_2 \text{ and } D=D_1 \text{ then } E=E_1\\
&\qquad\qquad\text{if } C=C_1 \text{ and } D=D_1 \text{ then } E=E2\\
&\qquad\qquad\qquad\text{if } D=D_2 \text{ then } E=E_3
\end{aligned}
\tag{24}
$$

where $A=\{A_1, A_2, A_3\}$, $B=\{B_1, B_2, B_3\}$, $C=\{C_1, C_2\}$, $D=\{D_1, D_2\}$ and $E=\{E_1, E_2, E_3\}$. A and B are the linguistic variables of the inputs, C and D are that of the median variable and E is that of the output.

It is really a mess when looking at such a set of fuzzy rules. It could not be translate into a fuzzy relation R with easy. When the number of the fuzzy subsets of each variable and the number of the linguistic variables increase, obviously the difficulty goes to extreme.

It is obvious that the operator's description of the system's behavior may not always reflect the actual situation exactly by 100%. When a set of control rules is given, someone may ask such a question as: how much is each rule true or how much do you believe it? We will attach a number of percentage to each individual control rule. For example, if A then $B(0.8)$, where the number 0.8 is the reliability factor of the rule *"if A then B"*. In this case, the fuzzy relation theory is unable to model the fuzzy control rules.

To tackle the problems mentioned above, using TVFIN will be much more flexible and convenient than using the fuzzy relation R.

First, let's see how the TVFIN model the following inference sentences in the fuzzy control rules:

1). *if A then B(w)*.(see Fig. 8)

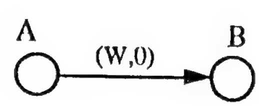

Fig.8

2). *if A then B and C(w)*.(see Fig. 9)

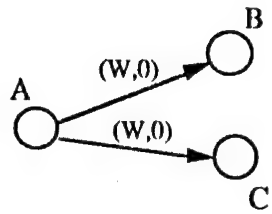

Fig. 9

3). *if A or B then C(w)*.(see Fig. 10)

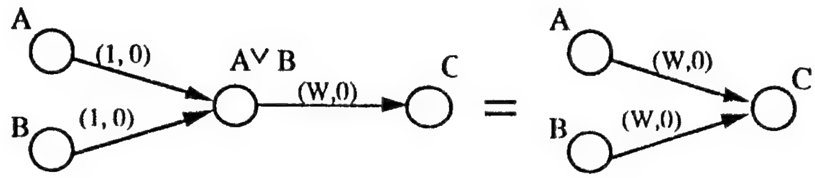

Fig. 10

4). *if A and B then C(w)*.(see Fig. 11)

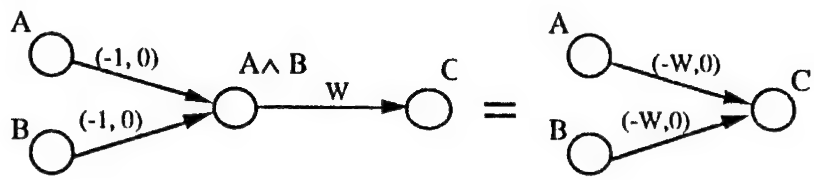

Fig. 11

5). *if not A then C(w)*.(see Fig. 12)

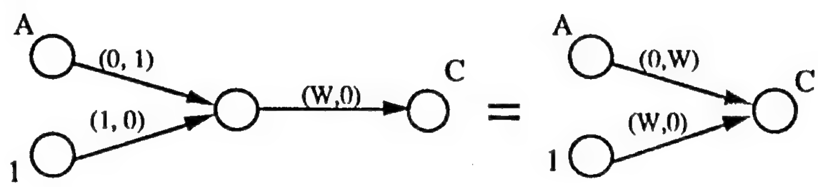

Fig. 12

Where the weight W is the certainty factor which represents the reliability of the rules.

Therefore, according to the definition of the TVFIN the fuzzy control rules in equ. (5) can be translated into a TVFIN as shown in Fig. 13. In Fig. 13, W_{ijk} is the weightage associated with the link connecting node $(A_i \wedge B_j)$ and C_k.

$W_{ijk} = 1$, when $\varphi(i, j)=k$; $W_{ijk} = 0$, when $\varphi(i, j) \neq k$.

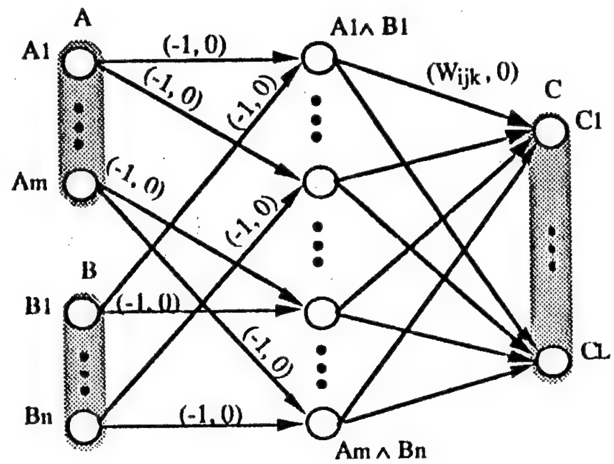

Fig. 13 The TVFIN of rules in (15)

If the input nodes are placed truth values, according to the rule of propagation, the truth values of the output nodes are:

$$\begin{aligned} C_k(u_o) &= \bigvee_{i,j} (A_i(x_o) \wedge B_j(y_o)) * W_{ijk} \\ &= \bigvee_{\varphi(i,\, j)=k} (A_i(x_o) \wedge B_j(y_o)) \end{aligned} \tag{25}$$

$$(i \in I, j \in J, k \in K)$$

where $A_i(x_o)$ and $B_j(y_o)$ are the truth values of the inputs and $C_k(u_o)$ is that of the outputs as shown in Fig. 14. We make a weightage sum of $C_k(u_o)$ as the defuzzified output of the fuzzy controller(see Fig. 14).

$$\begin{aligned} u_o &= \sum_{k \in K} C(u_o) * W'_k \\ &= \sum_{k \in K} \Big(\bigvee_{\varphi(i,\, j)=k} (A_i(x_o) \wedge B_j(y_o)) \Big) * W'_k \end{aligned} \tag{26}$$

$$(i \in I, j \in J, k=\varphi(i, j) \in K)$$

If we choose $W'_k = u_k$, the result of equ. (18) will be the same as that of equ. (13). This shows that the conventional inference method of fuzzy controller is a special case of the TVFIN.

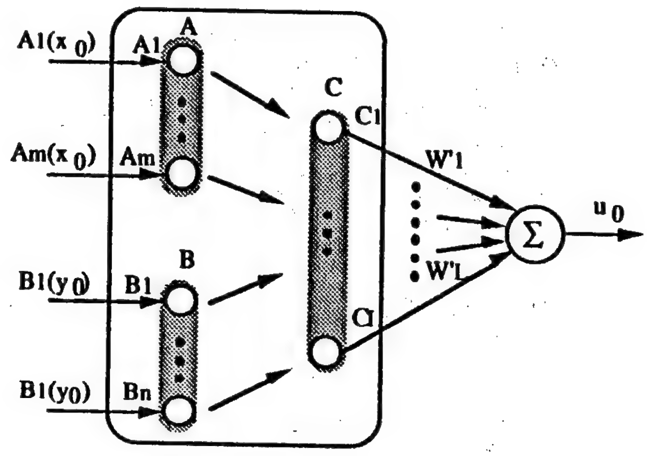

Fig. 14 The input and output of the TVFIN.

With the TVFIN, the set of fuzzy control rules in equ. (14) can modelled as Figure 15. If the truth values of the input nodes are given, the truth values of the output nodes can be calculated according to the rule of propagation of the TVFIN. The TVFIN overcomes the difficulty of the fuzzy relation which is hard to model fuzzy control rules like equ. (14). This means that the TVFIN can model control rules of any complication and any number of variables. This feature is especially useful in the knowledge representing in expert systems. It is very convenient to increase variables and/or rules, which is done by just adding some nodes and links to the old TVFIN. It is benefit when an expert system has to be renewed with new knowledge.

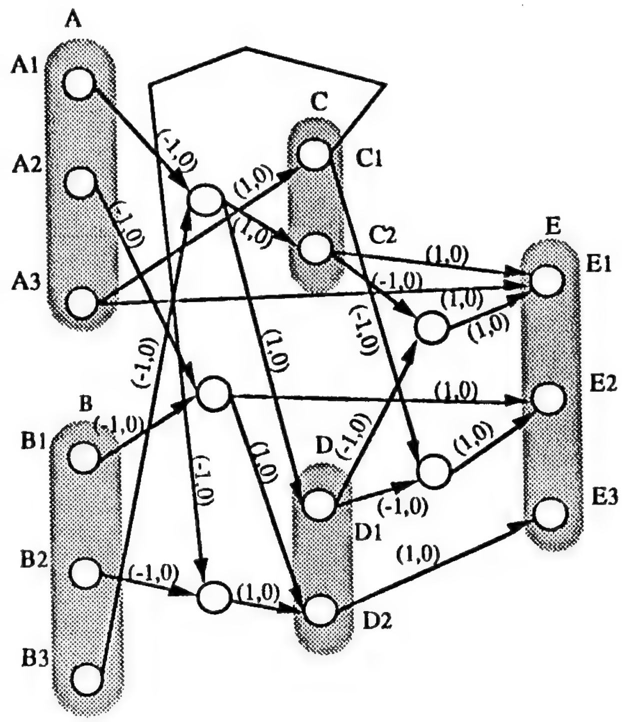

Fig. 15 The TVFIN of rules in equ. (24)

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NEURAL NETWORK FOR SHIP RECOGNITION

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ABSTRACT

In this paper, we proposed and simulated a practical approach to recognize ship silhouettes independently of translation, scale changes, rotation and any aspect angles using neural net The proposed neural network system consists of two subsystems. One is moment invariant subsystem and the another is a multilayered neural network that is tranined using quantum learning algorithm The simulated results show that this system can recognize ship silhouettes very correctly

INTRODUCTION

For recognizing ship silhouettes,required the ability to identify a specific ship as translates,changes scale or aspect angle. Many authers have studied this problem [1,3,4,5,6] ,but,all of approches they proposed are impractical for pattern recognition.A neural network can be trained to do this .However ,it required a very large number of training samples and the long training time.So,this method is impractical too. In this paper. We construct a system as shown in FIG.1.This systen can do this very well.The system consists of two subsystems,using moment invariants to perform preproceissing,and then,using multilayered neural network to perform ship silhouettes recognition,and to discriminate two somilar-looking ship silhouettes.

In FIG.1,the moment invariants are used to provide translation,scale change and rotation invarivnce,a small multilayerd neural network are used to provide aspect angle change invariance and give outputs of ship silhouettes recognition after the preprocessing which is performed by moment invariants.

THE MOMENT INVARIANTS

Given a two-dimensional image density distribution f (x,y) .the discriptors used in [2] are functions of the moment m_{pq} defined by

$$m_{pq}=\sum_x\sum_y x^p y^q f(x,y) \qquad p,q=0,1,2,\cdots \qquad (1)$$

the central moments that have the property on translation invariance are given by

$$T_{pq}=\sum_x\sum_y (x-\bar{x})^p(y-\bar{y})^q f(x,y) \qquad (2)$$

where $\bar{X}=\frac{m_{10}}{m_{00}}$, $\bar{Y}=\frac{m_{01}}{m_{00}}$.

The following functions R(1), R(2), R(3), R(4), R(5), R(6), R(7), are

invariant under translation and rotation

$$R(1) = T_{20} + T_{02} \quad (3)$$

$$R(2) = (T_{20} - T_{02})^2 + 4T_{11}^2 \quad (4)$$

$$R(3) = (T_{30} - 3T_{12})^2 + (3T_{21} - T_{03})^2 \quad (5)$$

$$R(4) = (T_{30} + T_{12})^2 + (T_{21} + T_{03})^2 \quad (6)$$

$$R(5) = (T_{30} - 3T_{12})(T_{30} + T_{12})((T_{30} + T_{12})^2 - 3(T_{21} + T_{03})^2)) + (3T_{21} - T_{03})(T_{21} + T_{03})(3(T_{30} + T_{12})^2 - (T_{21} + T_{03}))^2) \quad (7)$$

$$R(6) = (T_{20} - T_{03})((T_{30} + T_{12})^2 - (T_{21} + T_{03})^2) + 4T_{11}(T_{30} + T_{12})(T_{21} + T_{03}) \quad (8)$$

$$R(7) = 3(T_{21} - T_{03})(T_{30} + T_{12})((T_{30} + T_{12})((T_{30} + T_{12})^2 - 3(T_{21} + T_{03})^2) - (T_{30} - 3T_{12})(T_{21} + T_{03})(3(T_{30} + T_{12})^2 - (T_{21} + T_{03})^2) \quad (9)$$

The functions R (1) , . . . , R (7) can be normalized to make them invariant under a scale change by substituting the nomalized central moments Q_{pq} for T_{pq}. Q_{pq} is as

$$Q_{pq} = \frac{T_{pq}}{T_{00}}$$

where (p + q) / 2 + 1

NEURAL NETWORK TRAINING

Neural network is used to preform aspect angle changes invariance and give the output of ship recongition. The neuron used in neural network are same. The output of one neuron maybe written as follows [7] :

$$O_i = F(net_i) \quad (11)$$

$$net_i = \sum_j W_{ij} O_j \quad (12)$$

$$F(z) = \frac{1}{(1 + e^{-z})} \quad (13)$$

The training algorithm for this neural network may be written as follows

$$W_{ij}(n+1) = W_{ij}(n) - k\nabla E(W_{ij}(n)) + C(N_{n+1} - N_n) \quad (14)$$

where E is output error, C is parameter as temperature in Boltzmann machine, it must be reduced to zero slowly. N is normal -- dimensional Wiener process.

SIMULATION RESULTS

The proposed system can be used to recognize ship silhouettes. The simulation system is shown in FIG.2. The ship silhouettes are used to recognize are USDDG51 warship and USSR"KALAR"warship photos as shown in FIG.3.

After system is trained, it can be used to recognize ship silhouettes independently of scale changes, translation, ro tation oraspect angle. FIG.4 shows the simulation results.

From FIG.4, for DDG51, when recognizing ship from the side, the output of system is (0.94, 0.07); when recognizing ship from the top, the output of system is (0.89, 0.10), that means the system recognizes that ship is DDG.51 but something little like "KALAR".

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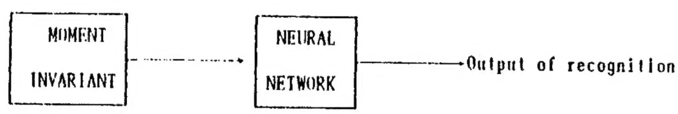


FIG.1 Architecture of system

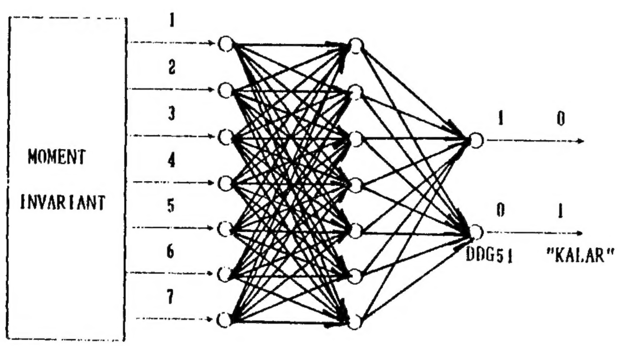


FIG.2 Simulation Architecture

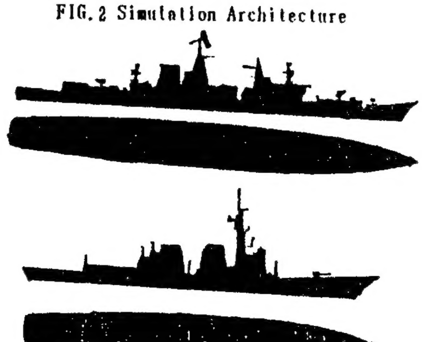
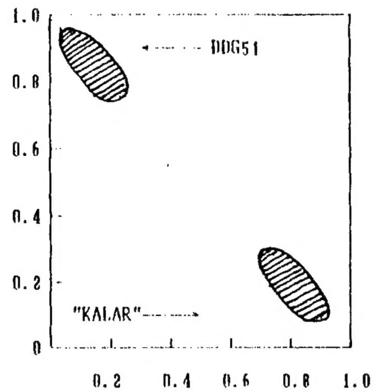


FIG.3 Training Samples



In FIG.4 the elliptical areas show the recognition output of system for DDG51 and "KALAR", respectively.

FIG.4 Simulation results

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